The Effect of Workplace Inspections on Employment and Sales – A Regression Discontinuity Analysis

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The mission of the US Occupational Safety & Health Administration (OSHA) is to generate safety and health regulations for the workers of America. From 1999 to 2014, OSHA operated the Site-Specific Targeting (SST) Program, with the purpose of targeting inspections on hazardous workplaces. The program collected data on cases that involve days away from work, job restrictions, and job transfers (DART) per establishment, and created a cutoff to inspect more "hazardous" workplaces through random assignment of inspections. Many studies have previously discovered that inspections reduced the DART rate in the years after the inspection was conducted. Using the regression discontinuity design, this paper examines the impact of inspections on employment and sales of establishments just above and below the SST-assigned cutoff. The dataset observes inspections performed from 2004 to 2011, from a total of 119,174 establishments. I compare establishments within a bandwidth close to the SST cutoff. The results suggest that having a DART rate just above the cutoff (which increases the share inspected) does not create a statistically detectable effect on the establishment's employment or sales.

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Introduction

In 2017, the total estimated cost for work-related injuries in the United States amounted to $161.5 billion (National Safety Council, 2017). A total of 104,000,000 days were lost during the year as a result of injuries from 2017 and previous years. The National Safety Council estimated that the days lost from job injuries will continue to remain at a high rate for the years ahead. The true cost to the nation, employers, and individuals of work-related injuries and deaths greatly exceed the cost of workers' compensation insurance alone, thus poses several issues for both the individuals and the institutions. Although each year the government agencies spend billions of dollars to enforce health and safety regulations through industry inspections, there exists several financial and empirical constraints to the policy. Studies in this field have discovered that most inspections target high-risk establishments (Kniesner et al. 2014), which creates a negative correlation between the rate of inspections and worker safety. An increase in inspection decreased the rate of cases that involve days away from work, job restrictions, and job transfers in the years after the inspection cycle (Li et al. 2019). Overall, inspections reduced serious injuries by an average of 9% over the following five years (Levine et al. 2019).

This paper acknowledges studies that have discovered an impact of inspections on work place injury rates, and takes a step further to analyze the effect of establishment inspections on employment and sales. I examine Occupational Safety and Health Administration (OSHA)'s Site Specific Targeting (SST) program which targeted inspections on hazardous workplaces. This research calculates any discontinuous trends in employment and sales for establishments just above and below the SST cutoff. Each year, OSHA used the data collected by the OSHA Data Initiative (ODI) and calculated the rate of cases that involve days away from work, job restrictions, and job transfers (DART) to construct case-rate DART cutoffs. Establishments with DART rates above the highest cutoff were categorized into the primary inspection list, the ones between the second-highest cutoff and the primary cutoff were assigned to the secondary inspection list, and so on. According to data calculations, establishments just above and below the cutoff did not differ significantly in their characteristics, but establishments in the primary inspection list were more likely to be inspected than those in the secondary list. With these frameworks, I use a regression discontinuity analysis to observe any discontinuous trends in establishment employment and sales for the workplaces just above and below the cutoff during the years 2004 to 2011.

Many studies on OSHA inspections and worker safety have examined the relationship between inspection and injury rates, with various methods that analyze the direct effects, alternative outcomes with technology, firm size, treatment, and types of injuries. Studies also underscore the importance of programs like the SST, because workplace injuries impose an exceptional burden on the US economy (Levine, et al. 2019). However, those studies have not conducted research on the relationship between inspections and employment/sales. This paper closely follows literature that evaluate the impact of OSHA inspections on establishments, which further provides relevant methods and data for researching the effect on employment and sales. Li and Singleton (2019) use a regression discontinuity design to address OSHA's new SST Plan and find that inspections decrease cases that cause days away from work, with changes most evident in certain sectors such as manufacturing. Levine, Toffel, and Johnson (2012) discover that inspections reduced injuries by 9.4%, and address counterfactual targeting rules that OSHA could have deployed. A limitation of their research is that their data was restricted to high-risk industries in California, whereas my paper observes data across various states and industries in the United States.

Some studies discovered minimal impact of inspections on injuries (Bartel and Thomas 1985; Viscusi 1986; Ruser and Smith 1991). Others have found that OSHA inspections at the federal or state level both reduce injury rates (Gray and Mendeloff 2005; Haviland et al. 2012). A couple of research focus on the relationship between inspection and timing, concluding that establishments inspected earlier in the year had extra time to circumvent workplace hazards (Smith 1979), and that inspections did not yield a statistically significant decrease in work-place injuries during the corresponding year of inspection (McCaffrey 1983). I also follow studies from Hahn, Todd, and van der Klaauw (2001), Rettore and Weber (2009), and Imbens and Lemieux (2008), which provide guidance to regression discontinuity identification and estimation.

In this study, I use a fuzzy regression discontinuity model to discover the effect of establishment inspections on employment and sales. Receiving a label as a "dangerous establishment" and being exposed to more frequent inspections could be unfavorable for both the establishment and their workers if it reduces sales or employment. Therefore, revealing the effects of inspections could help propose ideas to more effectively allocate workplace resources and improve establishment performance and their working environments.

Background

The Occupational Safety and Health Administration (OSHA) was created with the passage of the Occupational Safety and Health Act in 1970, with the purpose of generating a safer working environment for American workers. The SST program was initiated from 1999 to 2014, and used the data collected by the OSHA Data Initiative (ODI) to target establishments with high rates of injuries and accidents. OSHA established the SST program to prioritize inspections to establishments with "serious health and safety problems" (US Occupational Safety and Health Administration 2004). Each year, the ODI collected injury data from 60,000 to 80,000 establishments, and the following year it created a SST target list that categorized establishments with the highest injury rates (Levine et al. 2019). ODI used Form 300, which allowed employers to record cases related to death, days away from work, job restrictions or transfers, or medical attention beyond first aid. To identify and target highly dangerous establishments, the SST plan utilized case-rate cutoffs (Li et al. 2019). The plan designated a DART rate which created two main inspection cutoffs: the primary inspection list and the secondary inspection list. The higher cutoff was assigned to the primary inspection list, which included establishments with the highest injury rates averaging approximately five times the national average. The lower cutoff was assigned to the secondary inspection list, with establishments averaging approximately three times the national average injury rate (Levine et al. 2019).

For many years, OSHA assigned inspections via random assignment, which made it possible for researchers to discover a relationship between inspections and workplace injuries. Understanding the effects of the SST program is important because workplace safety regulators in the U.S. could inspect less than 1% of their target establishments due to most regulatory agencies facing severe budget constraints (US Occupational Safety and Health Administration 2017). Not only are executing the inspections costly, but the injuries that occur from dangerous firms also incur substantial costs. The Bureau of Labor Statistics announced that in 2018, there had been approximately 900,000 annual number of injuries that resulted in days away from work (DAFW), and the total workplace injuries added up to costing approximately $170 billion to the United States (National Safety Council, 2018). Therefore, establishing an effective policy regime to allocate the limited budget and resources towards a more accurate method of targeting industries with higher injury rates will be beneficial for both the industries and the workers, which can subsequently impact other outcomes including employment and sales.

Methodology

The objective of this study is to identify the effect of establishment inspections on employment and sales. I started with the dataset from Levine, Toffel, and Johnson (2019). I extracted the relevant variables and calculated the respective DART per establishment each year. The DART cutoffs provided by the SST program made it possible to sort establishments to either primary or secondary inspection list of that corresponding year.

The regression discontinuity model that I adhere to has been defined as "quasi-experimental" since its inception in Thistlewaite and Campbell (1960), due to its nature of its almost randomized methods. Using the fuzzy regression discontinuity design, I examine the change in employment and sales of the establishments at the cutoff.

Calculating DART

Using the data on establishment injuries and employee hours worked, I calculated the DART rate for each establishment and compared it to the DART cutoff of the corresponding year. The following equation for calculating DART was provided by OSHA.

- Days Away Restricted Transferred (DART) Rate = (N ÷ EH) x (200,000), where N is the number of cases involving days away and/or restricted work activity, and/or job transfer. EH describes the total number of hours worked by all employees during the calendar year, and 200,000 is the base number of hours worked for 100 full-time equivalent employees (OSHA 2007).

Fuzzy Regression Discontinuity

The main purpose of a regression discontinuity (RD) design is to identify the effect that the treatment variable X has on the outcome Y. A strength of using this design is that, provided that outside factors do not manipulate the variables, the assignment of the policy is likely to portray randomness near the cut-off (Smith et al. 2017). In the case of a sharp RD design, the probability of treatment jumps from 0 to 1 when X crosses the threshold c. The fuzzy RD design is different in that it allows a smaller jump in the probability of assignment to the treatment at the threshold (Hahn et al. 2001). The fuzzy RD only requires the condition shown in equation (1), where X indicates the

$$\lim_{\varepsilon \downarrow 0} Pr[D = 1|X = c + \varepsilon] \neq \lim_{\varepsilon \uparrow 0} Pr[D = 1|X = c + \varepsilon] \tag{1}$$

running variable, which effects the treatment variable, D. Because the probability of treatment increases by less than one at the threshold, the treatment effect can be calculated by equation (2),

$$\eta_F = \frac{\lim_{\varepsilon \downarrow 0} E\,[Y|X = c + \varepsilon] - \lim_{\varepsilon \uparrow 0} E[Y|X = c + \varepsilon]}{\lim_{\varepsilon \downarrow 0} E[D|X = c + \varepsilon] - \lim_{\varepsilon \uparrow 0} E[D|X = c + \varepsilon]} \tag{2}$$

which divides the jump in the relationship between the outcome variable Y and X at the threshold c by the discontinuity jump in the relationship between D and X (Lee et al. 2010). The subscript F refers to the fuzzy RD design.

Referring to the original FRD assumption model shown in equation (1), I restructured the equation to fit the specific case of this study. Equation (3) indicates that the probability of treatment increases at the cutoff c, in which this case is the DART cutoff for the corresponding year. The FRD

$$\lim_{\varepsilon \downarrow 0} E\left[D_i \middle| X_{i,t} = c + \varepsilon\right] > \lim_{\varepsilon \uparrow 0} E\left[D_i \middle| X_{i,t} = c + \varepsilon\right] \tag{3}$$

model assumes that despite the discontinuity in inspections at the cutoff, the conditional mean functions $E[Y(0)|X_i = x]$ and $E[Y(1)|X_i = x]$ are continuous (Hahn et al. 2001). This assumption can be supported in two ways: showing a smooth DART rate density near the cutoff, and that establishments just above and below the cutoff are similar in characteristics, which is further examined in the data summary section.

Data

During the years when SST program was in place from 1999-2014, the main purpose of the program was to promote “the most effective use of OSHA’s limited resources” (ERG and National Opinions Research Center 2009). Each year from 1996 to 2011, the ODI surveyed approximately 60,000 to 80,000 establishments. Annual DART/DAFWII were published yearly, which designated establishments to the primary or secondary inspection list under the SST program. The empirical analysis for this study refers to an establishment-by-year panel dataset constructed by Levine, Toffel, and Johnson (2019). From the dataset, I generated the DART rate for each establishment by using the data on injuries and total number of hours worked with the DART formula provided by OSHA.

Variables

Of the original dataset, I organized the variables: establishment ID, year, employment, sales, injuries, and whether the establishment was on the primary/secondary list. There were initially 3,172,701 observations of establishments by specific year, with the years ranging from 1989 to 2013. Once I generated the DART value per establishment, there were several outliers which were skewing the data set. The 99th percentile value for DART was approximately 34.2, but the largest DART value was 37974.68. Therefore, I compressed the DART values to 34.2 if DART > 34.2. In this process, observations were dropped if establishments had missing values of injuries and/or employee hours worked, which is the data necessary to compute the DART rate.[1]

[1] Days Away Restricted Transferred (DART) Rate= 200,000 x (Number of cases involving days away and/or restricted work activity, and/or job transfer)/ (Total number of hours worked by all employees)

Table 1 shows the yearly DART cutoff values for the primary SST target list provided by OSHA. Most DART cutoffs were 11 or 12, and from 2009, OSHA implemented a new cutoff regime that differed between industries of manufacturing, nursing, and others.

Table 1. Primary SST Target list cutoffs

Years	DART cutoff
2004	12
2005	12
2006	12
2007	11
2008	11
2009	Mfg=8; Nsg=17; Non-Mfg/Nsg= 15
2010	Mfg= 7; Nsg= 16; Non-Mfg/Nsg= 15
2011	Mfg= 7; Nsg= 16; Non-Mfg/Nsg= 15

Note: The data is collected from the official OSHA SST targeting data published on their website. The dataset expands over the years 2004 to 2011, which were the years that I could obtain relevant data. From the year 2009, the criteria for the primary inspection list changed, with different values of DART cutoffs used for specific industries. Mfg indicates establishments in the manufacturing sector, Nsg indicates nursing, and Non-Mfg/Nsg denotes establishments not in either of those two industries.

I also generated the variable, "DART-Cutoff", which indicates how far away the individual establishment's DART rate was from the target year's cutoff in that industry. I then calculated the changes in employment and sales to run a RD regression with the DART-Cutoff variable. The main RD model incorporates several time lags between the collection of the data and to its implementation, which is further specified in the *Model* section. After sorting out the variables, the effective dataset for establishments and DART cutoffs ranged across years 2004 to 2011. Reorganizing reduced the final dataset to a total of 320,582 number of DART observations across all years, which came from 119,174 unique establishments.

Model

For estimation, I use nonparametric, local linear regression to estimate the effect of inspections on employment and sales. I chose four years of lag from the DART collection to its effect to show up on changes in employment and sales, because there was a lag of two years in the collection of the establishment's DART to its implementation with the targeting cutoff (Li et al. 2019), and then I chose another two years to calculate the change in employment and sales. For instance, the DART data collected in 2002 were used to target inspections in 2004, and I observe the changes in employment and sales during the years 2004 and 2006. The main model that describes the effect of inspections on percent change in employment is:

$$\%\Delta Y_{i,\tau+4} = \alpha + \eta D_i + \beta\,(X_{i,\tau} - c_\tau) + u_{i\tau} \tag{4}$$

where $\%\Delta Y_{i,\tau+4}$ describes the percent change in employment from year $\tau + 2$ to $\tau + 4$, and η is the FRD estimand. D_i is a dummy variable indicating 1 if the establishment was above the DART cutoff, and 0 if below. $(X_{i,\tau} - c_\tau)$ is the running variable that denotes the distance between the collected establishment's DART value and that year's cutoff, c. $u_{i\tau}$ is the error term. Rewriting this formula with the variables labeled, the model becomes equation (5):

$$\%\Delta\, Y_{i,\tau+4} = \alpha + \eta D_i + \beta\,(DART_{i,\tau} - Cutoff_\tau) + u_{i\tau} \tag{5}$$

$\%\Delta Y_{i\tau}$ is calculated by using the outlier-robust formula (6). The model for the effect of inspections on sales is the same as equation (6), with the variable $Z_{i,\tau}$ substituted for $Y_{i,\tau}$.

$$\Delta Y_{i,\tau} = \frac{Y_{i,\tau} - Y_{i,\tau-2}}{0.5 \cdot (Y_{i,\tau} + Y_{i,\tau-2})} \tag{6}$$

Also, $D_i = 1(DART_{i,\tau} - Cutoff_\tau \geq 0)$, where the variable $(DART_{i,\tau} - Cutoff_\tau)$ calculates how far away the establishment DART rate is from the DART cutoff with lags in years. The treatment variable D is explained in equation (7), which identifies whether the establishment was above the

$$(DART_{i,\tau} - Cutoff_\tau) \quad \begin{cases} = 1 \text{ if value is greater than or equal to 0} \\ = 0 \text{ if value is less than 0} \end{cases} \tag{7}$$

DART cutoff or below it, and helps distinguish establishments in the primary or secondary inspection list.

For robustness check, I ran regressions to confirm that the FRD assumptions were satisfied, and calculated the outcomes with different RD bandwidths near the DART cutoff to identify any significant changes in the result.

Sample Summary

This study compares the changes in employment and sales of establishments just above and below the primary cutoff. As shown in Table 2, the dataset includes a total of 320,582 observations from 119,174 unique establishments during the year 2004 to 2011. The values of TC (Total cases of days away/restricted work activity/job transfer in calendar year τ) and THW (Total hours worked by all employees in year τ) were used to calculate DART, which had the mean of 4.19. The mean value

Table 2. Summary Statistics (2004-2011)

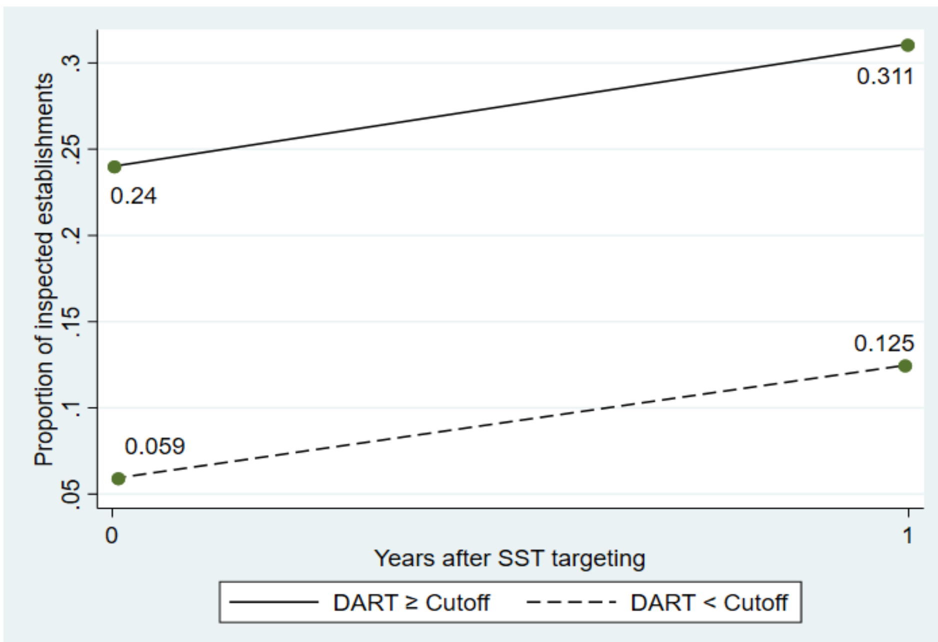
Variable	(1) Mean	(2) SD	(3) Min	(4) Max
TC	5.36	15.06	0	1191
THW	267028.5	3430898	1	1.76E+09
DART	4.19	4.98	0	34.2
Dart-Cutoff	-6.07	5.1	-17	27.2
Dart-Cutoff (if DART ≥ Cutoff)	4.89	5.06	0	27.2
Dart-Cutoff (if DART < Cutoff)	-7	3.14	-17	-0.0004
Employment	129.34	326.315	1	48200
Sales	1.84E+07	5.41E+07	0	7.88E+09
%Change in employment (τ+2 to τ+4)	0.025	0.286	-1.998	1.998
%Change in sales (τ+2 to τ+4)	0.052	0.337	-2	2
Total # of observations	320,580			
# of observations (Dart ≥ Cutoff)	34,495			
# of observations (Dart < Cutoff)	286,087			
# of establishments	119,174			

Notes: Sample is derived from the dataset of Levine, Toffel, and Johnson (2019), and consists of establishments observed at least twice, with the two observations of employment and sales spaced two calendar years apart. TC stands for the total cases of days away/restricted work activity/job transfer in a calendar year *τ*. THW is the total of hours worked by all employees in year *τ*. DART is compressed so large outliers are adjusted to 34.2. The values for percent changes in employment and sales in years τ+2 to τ+4 are adjusted to the scale of -1 to 1. For instance, a change of 0.025 in employment is equivalent to a 2.5% change.

of the distance of the establishments' DART from the cutoff was -6.07, with its average value being 4.89 for establishments above the cutoff, and -7 for the ones below the cutoff. According to the statistics, only 10.76% of observations during the year 2004 to 2011 had exceeded the cutoff. The values for percent change in employment and sales during years τ+2 to τ+4 were adjusted to the scale of -1 to 1. The mean percent change in employment and sales at were each 0.025 and 0.052, which is equivalent to a 2.5% and 5.2% change.

To show that the initial stage of the treatment effect is valid, I calculated the SST inspection rates and confirmed that establishments just above the cutoff were more likely to be inspected under the SST program. Figure 1 shows the proportion of inspected establishments, starting from the target

Figure 1. SST Inspection Rates by Year Relative to Target Year

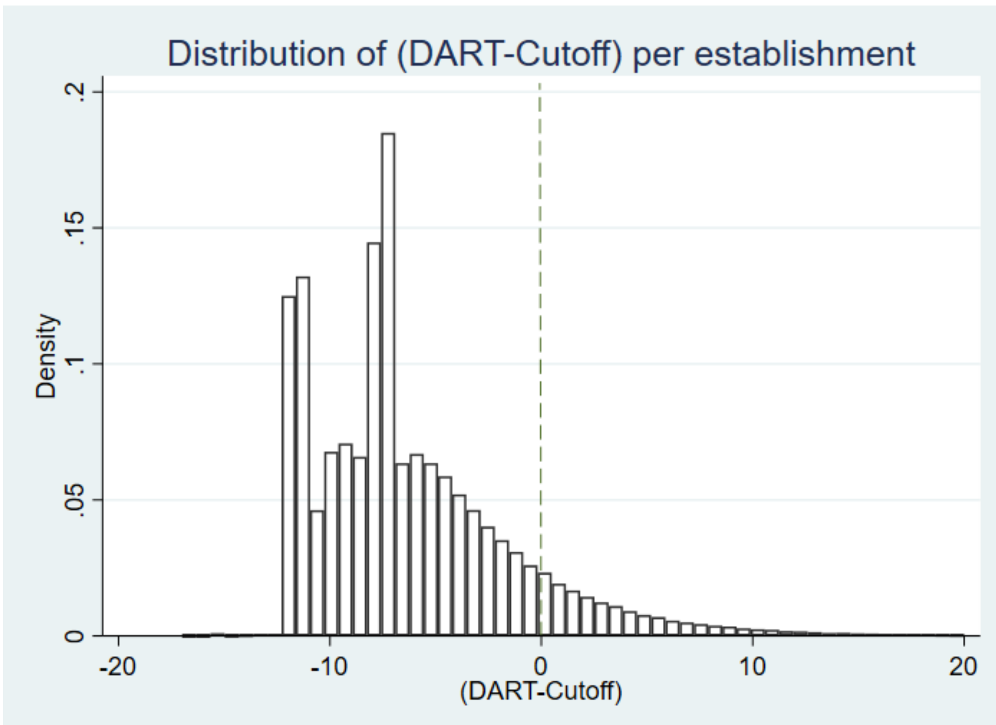


Notes: Sample consists of establishments observed at least twice and with baseline DART within 0.5 of the primary list cutoff. Year 0 reflects the year of DART targeting, which is 2 years after the establishment data were collected. The solid line and dashed line represent establishments with DART rates just above and below the DART cutoff.

year (0) to the next year. Only 5.9% of establishments with DART rates below the cutoff were inspected in the beginning year, in comparison to a 24% inspection rate for establishments with DART rates above the cutoff. In the year after the initial SST targeting, the proportion of inspected establishments also showed a large gap between the establishments just above and below the DART cutoff, with a difference of 18.6 percentage points.

To assure that the dataset complies with the RD assumptions, I first checked that the conditional mean functions $E[Y(0)|X_i = x]$ and $E[Y(1)|X_i = x]$ were continuous at the cutoff. Figure 2 shows the density of the value, DART-Cutoff. The graph confirms that the density of the

Figure 2. Distribution of Establishment (DART-Cutoff)



Notes: The graph shows a density distribution of (DART-Cutoff) per establishment. Bin width = 0.6.

DART rate is smooth near the cutoff. The smooth trend of the distribution suggests that establishments did not manipulate their DART rates around the cutoff to avoid inspection, which seems reasonable since establishments reported their DART rates before the SST cutoffs were announced.

The second assumption of FRD indicates that the establishments just above and below the cutoff should show similarity in observable characteristics such as employment and sales, before being assigned to inspection. Table 3 shows the regression discontinuity analysis of natural log values of employment and sales of establishments just above and below the DART cutoff, prior to inspection. The data suggests that there is not a significant difference between the values of employment and sales for establishments just above and below the cutoff. At the DART cutoff, there was approximately 4.76% discontinuity in employment and -1.35% discontinuity in sales, but these

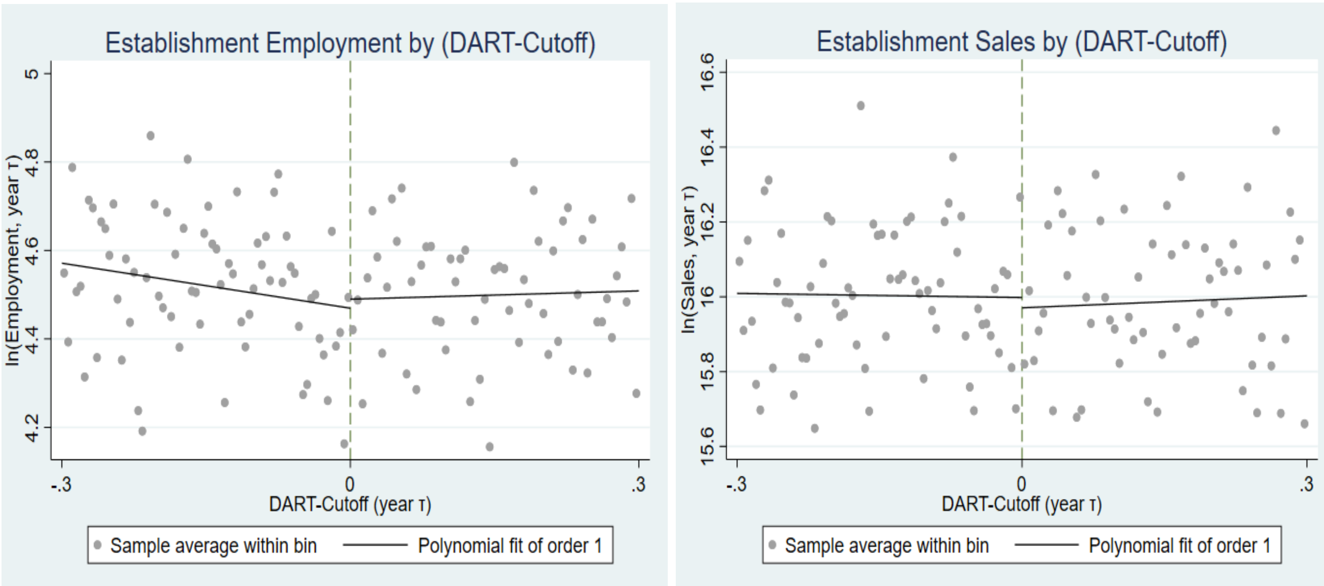
Table 3. RD Employment and Sales by (DART –Cutoff) Prior to Inspection

	(1)	(2)
VARIABLES	*ln*(Employment)	*ln*(Sales)
RD Estimate	0.0476	-0.0135
	(0.0439)	(0.0624)
Bandwidth estimate	0.3	0.3
Effective # of observations left of cutoff	2351	2351
Effective # of observations right of cutoff	2184	2184
Observations	4535	4535

Notes: Sample is derived from establishments with DART rates just above and below the DART cutoff, by using a bandwidth of 0.3. N= 4535. The variables are employment and sales in the natural log form. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

values were statistically insignificant. To more efficiently visualize the RD estimates of Table 3, Figure 3 has translated the outcomes into RD graphs. Both axes have gathered values from year τ, which implies that the results show trends before inspections, since the effect of DART targeting on employment or sales could be visible only after year τ. Consistent with the discontinuity estimate results from Table 3, the graphs show a minimal effect of (DART-Cutoff) on the establishments' employment and sales before the inspections were conducted.

Figure 3. RD Employment and Sales by (DART –Cutoff) Prior to Inspection



Notes: Sample is derived from establishments with DART rates just above and below the DART cutoff, prior to being inspected. The horizontal axis indicates the distance of the establishment's DART rate from the cutoff in year τ, and the vertical axis each represent employment and sales in the natural log form.

Results

With the major assumptions of FRD and treatment effects addressed, it is possible to take the final step of calculating the estimate of the discontinuity in the change in employment and change in sales respective to the cutoff. Table 3 presents the estimated discontinuity and the bandwidth using local linear regression. As shown, the cutoff is associated with an approximate 0.629% increase in employment, and 2.09% increase in sales, which are both statistically insignificant. This suggests that having a DART rate just above or below the cutoff does not statistically significantly impact the establishment's employment or sales.

Table 3. RD Change in Employment and Sales by (DART-Cutoff), Years $\tau + 2\ to\ \tau + 4$

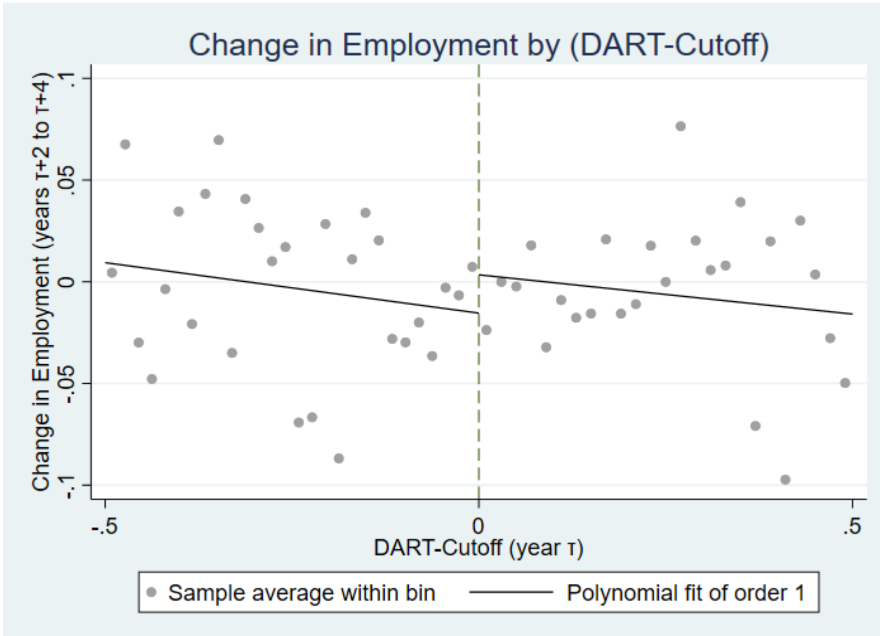
	(1)	(2)
VARIABLES	Change in Employment	Change in Sales
RD Estimate	0.00629	0.02088
	(0.1746)	(0.03044)
Bandwidth estimate	0.5	0.5
Effective # of observations left of cutoff	669	669
Effective # of observations right of cutoff	624	624
Observations	1293	1293

Notes: Sample is derived from establishments with DART rates just above and below the DART cutoff, by using a bandwidth of 0.5. This process restructured the original dataset to observe a total of 1293 observations. The estimates for change in employment and sales during years τ+2 to τ+4 were adjusted to the scale of -1 to 1. A 0.00629-point change is equivalent to a 6.29% change. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure 4 and 5 plots these results into a RD graph to visualize the insignificant discontinuity at the cutoff. Figure 4 illustrates some discontinuity at the cutoff, but according to Table 3 this jump is not significant enough to suggest a relationship between inspections and changes in employment. Similarly, Figure 5 also presents some discontinuity at the cutoff, but the results from Table 3 reveals that this jump was equivalent to a 2.09% change in sales, which is statistically insignificant.

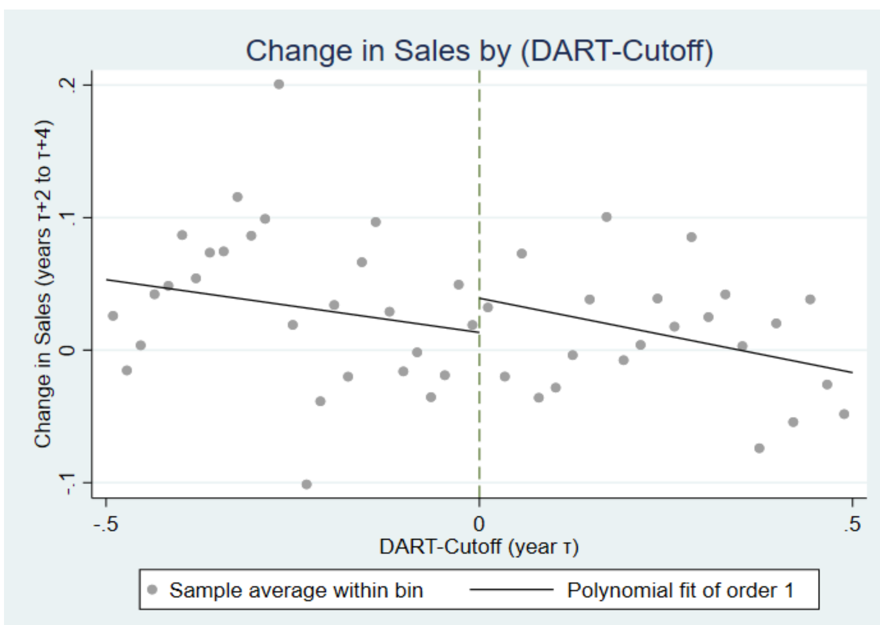
As a result, the total RD calculations points to the conclusion that although having a DART rate just above the DART cutoff categorizes the establishments into the primary list with a higher chance of inspection, it does not pose a significant effect on employment and sales.

Figure 4. RD Change in Employment by (DART-Cutoff)



Notes: Sample is derived from establishments with DART rates just above and below the DART cutoff, by using a bandwidth of 0.5. N=1293.

Figure 5. RD Change in Sales by (DART-Cutoff)



Notes: Sample is derived from establishments with DART rates just above and below the DART cutoff, by using a bandwidth of 0.5. N=1293.

Robustness Checks

In Table 4, I examine the robustness of the RD results with respect to different bandwidths. The original bandwidth used in Table 3 to calculate the RD estimate was 0.5, which provided 669 and 624 observations each to the left and right of the cutoff. This outcome of the RD analysis was statistically insignificant, which suggested that there was not a detectable causal relationship between the treatment and outcome variables. To assure that the results are not significantly different with other bandwidths, I selected a smaller bandwidth of 0.1 and a larger bandwidth of 1 to compare the RD analysis results. With the bandwidth of 0.1, the effective number of data observations had

Table 4. RD Change in Employment and Sales by DART-Cutoff and Bandwidth, years $\tau+2$ to $\tau+4$

VARIABLES	(1) Change in Employment	(2) Change in Sales	(3) Change in Employment	(4) Change in Sales
RD Estimate	-0.0225	0.00999	0.00458	-0.00722
	(0.0307)	(0.0461)	(0.0141)	(0.0229)
Bandwidth estimate	0.1	0.1	1	1
Effective # of observations left of cutoff	127	127	1380	1380
Effective # of observations right of cutoff	123	123	1203	1203
Observations	250	250	2583	2583

Notes: Sample is derived from establishments with DART rates just above and below the DART cutoff, by using a bandwidth of 0.1 and 1. This process restructured the original dataset to observe a total of 250 observations for bandwidth 0.1, and 2583 observations with bandwidth value 1. A 0.02-point change is equivalent to a 2% change. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

decreased to 127 observations to the left of the cutoff, and 123 observations to the right of the cutoff. As shown in columns (1) and (2), the smaller bandwidth of 0.1 yields RD estimates which are equivalent to a -2.25% change in employment and 0.999% change in sales, which are also statistically insignificant. In columns (3) and (4), the selected bandwidth estimate is 1, which increases the effective number of observations on both sides of the cutoff. The RD estimates with this cutoff also show statistically insignificant values of approximately 0.458% change in employment and -0.722% change in sales. Therefore, Table 3 and Table 4 show slightly different results in the RD estimates, however, the ultimate results all indicate that the estimates are statistically insignificant. This finding suggests consistency in the results which indicate that having a DART rate above the cutoff does not pose a notable effect on the establishment's employment or sales.

I selected 0.5 as the optimal bandwidth because the bandwidth of 0.1 does not generate enough observations, which can result in unwanted estimation bias. The bandwidth of 1 includes approximately twice as much observations those from bandwidth 0.5, but it captures establishments that are further away from the cutoff than with the bandwidth of 0.5. With these reasons, I selected the bandwidth to be 0.5. However, choosing a bandwidth was not a meaningful factor that altered the results because the RD estimates for all three different bandwidths turned out to be statistically insignificant.

Conclusion

This study addresses the impact of OSHA's SST inspection program on establishment employment and sales. The SST program has been running since 1999 to 2014, and recently OSHA has re-launched the program to target further reductions in industry injury rates. Closely referring to past literatures that examine the impact of inspections on other factors such as injury rates, my study adds to the existing literatures by addressing the inspection effects on other outcomes, including changes in establishment employment and sales. The research has limitations, including the effect of inspections beyond two years, which is not observed in the calculations. This can possibly lead to my results understating the actual effect of inspections on employment and sales in further years after SST inspection targeting. Also, it is possible that employers could change their behaviors once they signal an adjustment in the probability of establishment inspections. Such changes will likely have a minimal effect on the outcomes since the SST program targets inspections with data from two years prior, but these behavioral changes are not addressed in this study. With these limitations in mind, I find that having an establishment DART rate just above or below the SST targeting cutoff does not create a statistically detectable effect on the establishment's employment or sales.

The significance of this study is that it identifies that conducting inspections on workplaces does not directly impact workers or the workplace outputs in a negative manner. From previous years, adopting a policy to more efficiently allocate the limited inspection resources has become an important challenge. With the results of this study alleviating concerns of negatively impacting workers or workplace output through inspections, effective methods of targeting establishments with higher injury rates should be reviewed to favorably impact both the workers and the employers, and subsequently lower the total costs of programming inspections.

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